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Neural Network Analysis of the Causes of Vertical Split Rim Wheel Rim Failure

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Summary

The Transportation Technology Center, Inc. and Engineering Systems, Inc. examined the potential of neural network technology to identify vertical split rim (VSR) wheels operating in heavy-axle-load lines in revenue service on North American railroads.

A neural network model was designed and built to capture the complex relationships between input variables relevant to the wheel-operating environment, such as wheel impact load, axle position in the car, temperature, age, and one single output represented by wheel failure types, VSR or non-VSR. The model is used to predict VSR wheel failures.

Deploying the neural net model on 44 validation VSR wheels showed that the trained neural network model was successful in identifying VSR occurrence in 84.1 percent (70% to 93% due to small sample size) of the validation dataset. Deploying the same neural net model on 12 shelled wheels successfully identified all 12 as non-VSR wheels. The model performance was not as optimal on shattered rim wheels and was successful in identifying 6 of 12 shattered rims. The validation datasets for each wheel defect were fresh sets of data that were not used while training the neural network model.

Based on the neural net analysis with the amount of data assembled thus far, results show that:

- Wheel impact level is correlated to VSR failures, and not including such information as an input to the model will affect the prediction accuracy.
- Ambient temperature at or near the time of VSR formation has the least effect on VSR identification.
- The position of the wheelset in the car, wheel age, and tread hollowing are not significant factors for VSR identification.
- Wheel rim thickness data that was not available in the dataset may have an effect on VSR identification and should be investigated further.

Examining the neural net performance in this study concludes that the neural net technique may be a useful tool to adequately distinguish VSR wheel failures from other types of failures. However, further assessment is necessary to better understand the expected false positive and negative error rates of the model if deployed in a revenue service environment.

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INTRODUCTION

Although VSR failures are rare, they have become one of the leading causes of wheel failure in North American heavy-haul services. Figure 1 shows an example of a VSR wheel. VSRs initiate from wheel tread surface rolling contact shells. The VSR is propagated by brittle fracture with the loss of a significant portion of either the front or back of the rim. Most but not all VSRs are associated with high impact loads at the wheel/rail interface. Tread hollowing and low ambient temperatures have also been suggested as contributing factors in VSR failures. In order to determine the relative effect of each of the above factors, a neural network analysis has been applied.



Figure 1. VSR Failures

NEURAL NETWORK ANALYSIS

The neural net model was built to predict possible defective railcar wheels operating in revenue service. The aim of building the model was to adequately identify the wheels that could develop VSRs. An input/output database of wheels with various defects was established to train and validate the neural net model. Nearly half of the data cases available were used to build the neural net model and the remaining cases were used for validation. Validation data was not used while building the neural net model. Instead the following input variables were used:

- Ambient air temperature on the day of wheel removal
- Axle position in the car
- Wheel age
- Wheel tread hollowness
- Wheel impact load

The neural net model was trained to predict wheel defect types. The output variable was set to only contain two possible outcomes: VSR or non-VSR. The non-VSR wheels comprised shattered rim and shelled wheels.

An artificial neural net, such as the one built in this study, is a network of artificial neurons or nodes consisting of many input paths and one output path. Figure 2 shows a simplified architecture of a neural net.

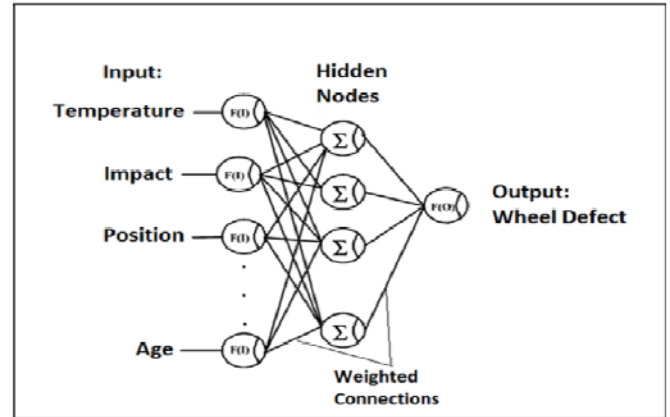


Figure 2. A Simplified Neural Net Representation

The nodes in neural nets can be connected in many ways. In this study, the architecture used to connect the nodes is multilayer perceptron (MLP). It consists of an input layer, two hidden layers, and an output layer. The input signal propagates through the network in a forward direction. To train an MLP, the back-propagation algorithm is used and is based on the error-correction learning rule. The rule applies forward and backward passes through all the network layers. In the forward pass, an input vector is applied to the nodes of the network, and the effect from applying that input vector propagates through the neural network layers. Thus, an output is produced as an actual response of the network.

If the network response is not adequately close to the desired response, a backward pass is used and the neural net weights are iteratively adjusted based on an error-correction rule to fine-tune the response in order to move it closer to the desired response.

Data

A review of the data before training and testing the artificial neural network provides some initial conclusions. Table 1 shows a summary of the data.

Table 1. Summary of Data

	Vertical Split Rim	Rolling Contact Fatigue Shells	Shattered Rims
Number	81	24	24
Average Temperature, F	50.54	61	51.4
Average Age, Yr	10.8	5	8.8
Average Hollow Tread, mm	0.54	1.1	0.9
Average Impact, kips	64	150.3	46.2

VSRs and shattered rims occur, on average, during the winter months. Additionally, VSRs and shattered rims tend to occur on older wheels and with impact levels of approximately the same magnitude. Conversely, the shelled wheels used in this analysis occurred during the summer at a younger age and produced larger impacts.

The data appears to contradict some initial observations of Berge that suggested VSRs occur due to bending stress when the wheel is riding on the field edge of the tread.¹ The moment arm provides a tensile stress on the tip of the shell crack, which could aid the VSR failure process. According to Kristan et al. once a small crack under a shell turns in an axial direction, only a small amount of growth can cause a VSR if a high enough stress is present, and VSRs tend to occur on wheels with tread hollowing.² There exists anecdotal reasoning that low ambient temperatures are associated with VSR formation, given that Canadian railroads appear to develop more VSRs per car than U.S. railroads. An examination was made of several aspects of VSR failures that occurred on a U.S. railroad.³ The study shows that the majority of VSR wheels had been producing impact loads, as Figure 3 shows.

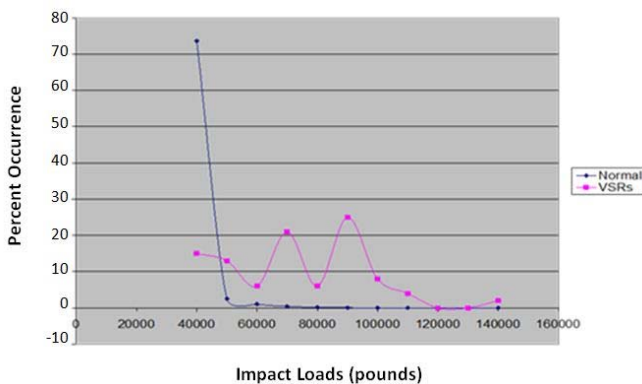


Figure 3. Impact Loads of Normal and VSR Wheels³

The majority of wheels in revenue service do not produce high impact loads, and the VSR and non-VSR failed wheels in the dataset are not intended to represent the typical wheel population.

The non-VSR wheels used in this analysis were selected for two reasons. First, the non-VSR wheels exhibited some traits that may have increased the likelihood that they would have become VSR wheels. Wheels with shells that produce very large impact loads would be exposed to large stresses in the rim that could potentially initiate or propagate VSR cracks. Shattered rims have been shown to initiate at material inconsistencies in the rim, and such stress risers could be potential VSR initiation sites. The second reason for using the wheels that comprise the non-VSR dataset is that the same data fields were kept on these wheels at the time of removal including the age of the wheel and a tread hollow measurement, thereby allowing the variables to be compared against the VSR dataset.

Lonsdale et al. attempted to determine if high impact loads are an element of VSR formation.⁴ Finite element results calculated surface tensile stresses of 29,007.5 psi for a new wheel and 56,999.8 psi for a worn wheel under a 200,000-pound impact, 1 inch from the front rim face. However, drop tests of 200,000 pounds did not produce a VSR fracture on a wheel that contained tread shell defects.

RESULTS

The first step in a neural network is a training or network teaching function followed by a validation step with the remaining failed wheels. Thirty-seven VSR (of 81 in dataset) and 24 non-VSR wheels (of 48 in dataset) were randomly selected from the database for the neural network training. The non-VSR wheels contained shattered rim and shelled wheels, 12 cases each. The neural net input variables selected were ambient temperature on the day of failure, and the position of the wheel in the car, age of the wheel, amount of tread hollowing, and the impact load were measured at the last passage over a wheel impact load detector. Figure 4 shows the results of deploying the model on 44 validation VSR wheels, and it also shows that the trained neural network model is successfully identifying VSR occurrences in 84.1 percent of the validation dataset. Due to the small sample size, the confidence interval of 84.1 percent is 70 to 93 percent.

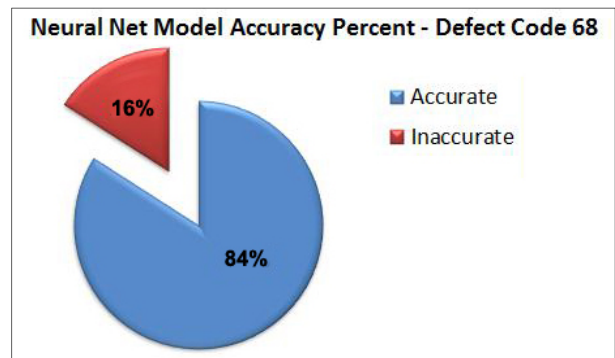


Figure 4. Results of the Neural Net Model on VSR Wheels

Deploying the same neural net model on the remaining 12-shelled wheels proved successful in identifying 100 percent of the validation dataset, as Figure 5 shows. For shattered rim wheels, the neural net model performance is not as optimal and is successful 50 percent, as Figure 6 shows. The validation datasets for each wheel defect were fresh sets of data that were not used while training the neural network model, and they were only used to assess the model performance. The model was most successful at identifying shelled and VSR wheel failures.

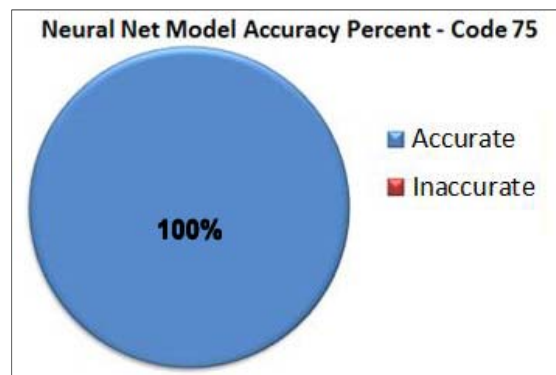


Figure 5. Results of the Neural Net Model on Shelled Wheels (non-VSR)

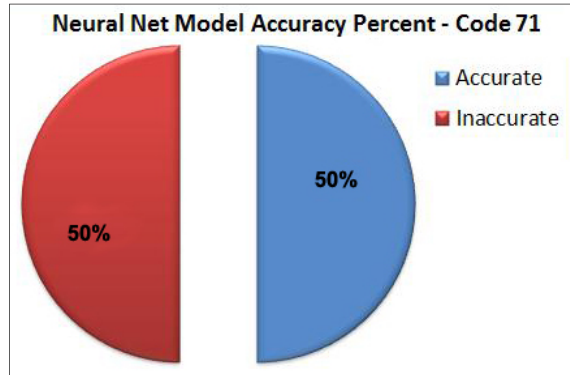


Figure 6. Results of the Neural Net Model on Shattered Rim Wheels (non-VSR)

The trained neural net model was then used to determine the relative effects of the failed wheel characteristics on the VSR wheel predictions. When the entire validation dataset was tested using the trained model, the following results showed that the neural network will again predict VSR formation 84.1 percent of the time. Each effect was then removed, in turn, from the training data, the neural network retrained without it and deployed on the same validation dataset to determine the relative effect of each input variable. Figure 7 shows the model performance results. The results show that the impact level is the most significant input variable to the model, and not including such information as an input to the model will affect the prediction accuracy. The position of the wheelset in the car, wheel age, and tread hallowing do not appear to make significant contributions to the accuracy of the model. The ambient temperature appears to be the least significant input variable to the model's accuracy. However, the combination of all the input variables, excluding the impact level, is capable of predicting VSR occurrence in 66 percent of the validation dataset. This suggests that those input variables may carry the information that contributes in enabling the model to recognize wheel failure patterns. No confidence intervals are provided by the neural network predictions.

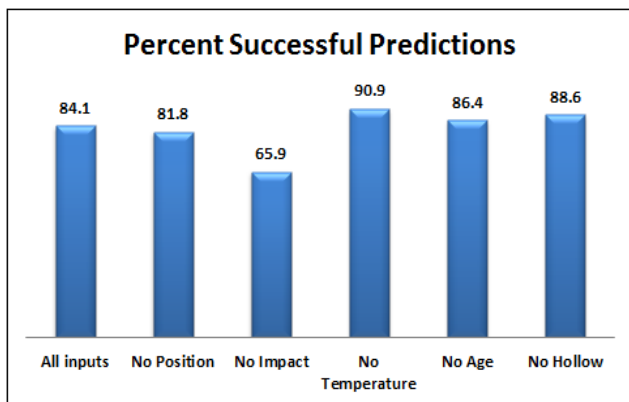


Figure 7. Effect of Individual Inputs on Accuracy of VSR Prediction

CONCLUSIONS

Based on the neural net analysis with the failure data assembled thus far, results show that:

- Wheel impact level is correlated to VSR failures.
- Ambient temperature at or near the time of VSR formation has the least effect on VSR identification.
- The position of the wheelset in the car, wheel age, and tread hollowing are not significant factors for VSR identification.

WAY FORWARD

The neural network technique used in this study shows, to a considerable extent, that it could be useful in classifying VSR failures. The presence of feature combinations pertinent to the different wheel failures in the database is valuable to the performance accuracy of the neural net model. Features such as impact load, wheel relative position in a car, and ambient temperature are readily available in near real-time. Tread hollowing and wheel age would be more difficult to incorporate in near real-time, but not impossible. Data representing a typical wheel population needs to be assembled and used as the non-VSR population to better understand the expected false positive and negative error rates of the model, if it is to be deployed in a revenue service environment.

Wheel rim thickness data that was not available in the dataset may have an effect on VSR identification and should be investigated further. Rim thickness may account for some of the 16 percent false predictions in the VSR and 50 percent false predictions in the shattered rim cases already reported.

REFERENCES

1. Berge, S. 2001. "Shell/Spall Basics," Presentation to the BNSF Wheel Study Group, Topeka, KA.
2. Kristan, J., D. H. Stone, and J. Elkins, 2004. "Effect of Wheel Loading on the Occurrence of Vertical Split Rim Wheel Failures," Paper IMECH2004-59049 In *Proc. of 2004 ASME International Mechanical Engineering Congress and Exposition, Rail Transportation*, Anaheim, CA.
3. Snyder, T.W., et al. 2008. "Characterization of Vertical Split Rim Wheel Failures," Presentation to the BNSF Wheel Study Group, Topeka, KS.
4. Lonsdale, C., T. Rusin, and T. Hay, 2009. "Research to Understand the Effects of Wheel Impact on Wheel Stress Levels," Paper JRC2009-63026 In *Proc. of 2009 ASME Joint Rail Conference*, New York, NY.